A Robust Feature Selection Method for Classification of Cognitive States with fMRI Data

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Abstract. The functional magnetic resonance imaging (fMRI) technique is a powerful imaging tool for analyzing the brain activity by localizing patterns of activity related to specific mental processes. Recently, researchers have started to solve the inverse problem of detecting the cognitive states at a particular point of time by applying the multi-voxel pattern classification approach. Since fMRI data are high dimensional, extremely sparse and noisy, feature selection is a key challenge in this kind of approach. In this paper, we propose a new method for selecting the most informative features from fMRI data. By computing Fisher Discriminant Ratio, we can identify the most active voxels from several Regions of Interest. These active voxels are considered as the most powerful discriminative features. We investigated the performance of this method by classifying the human's cognitive states of "observing a picture" versus "reading a sentence". The experimental results showed that our method achieved the highest accuracy compared to other feature selection methods with the Gaussian Naïve Bayes (GNB) classifier. The average accuracy of six human subjects is approximately 96.45%.

Keywords: fMRI, Regions of Interest, feature selection, Fisher Discriminant Ratio, active voxel.

1 Introduction

Neuroimaging is a key process to access the human's cognitive states through brain activation. In this domain, the functional magnetic resonance imaging (fMRI) has the promise of achieving good performance for studying human cognitive processes. fMRI technique is commonly performed using blood oxygenation level-dependent (BOLD) contrast to local changes in deoxyhemoglobin concentration in a brain [1]. Based on the diamagnetic property of oxygenated hemoglobin and paramagnetic property of deoxygenated hemoglobin, BOLD signals can construct the measurements of the activation of brain for generating three-dimensional images. Each image consists of a number of uniformly spaced volume elements, called voxels. If some parts of the brain are activated by mental states, the voxel's intensity will be changed.

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Tracking the variation of this value across time can get the knowledge of the brain's activation.

There are two main approaches for analyzing fMRI data: localization and classification. In the localization approach, researchers have to identify which regions of the brain are activated when a human performs a particular cognitive function. In contrast, many other researchers are interested in mapping from fMRI data to the human subject's cognitive states [2-7] which are known as classification problem. In this approach, a machine learning classifier is necessary to automatically detect the subject's cognitive state at a single time interval. This classifier needs support from a powerful feature selection method to deal with the issue of extremely high dimensional, sparse and noisy data. For example, in our case, we encountered problems where the examples are described by more than 80,000 features and we have only several dozens of examples per class. Selecting the most informative features from fMRI data will not only improve the accuracy of classifier but also reducing the processing time effectively.

In this paper, we propose a new method for selecting the most informative features from fMRI data. The main idea of our proposed method is to extract the most active voxels from the most active Regions of Interest (ROIs). These active voxels are considered as the most powerful discriminative features for the cognitive state classification. The activity of voxels was measured by the Fisher Discriminant Ratio. We performed classification of the human's cognitive states of "observing a picture" versus "reading a sentence". By using Gaussian Naïve Bayes classifier, our system achieved the average accuracy approximately 96.45%.

The remainder of this paper is organized as follows. Section 2 describes approaches of others researchers and their achievements. Section 3 discusses about the proposed method. The data description and experimental results are detailed in Section 4. Section 5 is our conclusion.

2 Related Work

Since fMRI data is high dimensional, dimensionality reduction is typically performed before classification to improve the performance of system. The Principle Component Analysis (PCA) and the Regions of Interest (ROIs) are two of the most well-known feature selection methods in the fMRI data analysis system. PCA is a conventional dimensionality reduction method that has been proved to be a powerful approach for many kinds of data mining analysis. However, when the dimension of original data is much higher than the number of observations which is the common case of fMRI data, PCA cannot achieve a good performance. Therefore, many researchers tried to apply the enhanced version of PCA or the combination of PCA and other techniques. T. Hoang et al. used incremental PCA (iPCA) to develop an incremental subspace tracking for reducing computation and storage requirements [3]. Y. Fan et al. applied PCA after extracting regional features which are formed by statistical information [4].

Brain regions that are relevant to the problem under study must first be selected from a background of brain activity [4]. Since only some specific regions of the brain are activated when a mental state is performed, selecting the features from restricted

Regions of Interest (ROIs) is a good approach. Etzel et al. tried to solve classification problem of fMRI by using anatomical ROIs [5]. They selected all voxels containing in some specific ROIs to evaluate the performance of anatomical ROIs-based fMRI classification approach. Mitchell et al. and S. Bapi et al. selected the most active voxels per ROIs [6,8]. They applied t-test for each voxel of each target class to measure the power of active voxels.

Instead of using standard classifiers such as Gaussian Naïve Bayes (GNB), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), Bernard et al. proposed a new group of classifiers, called Generalized Sparse Classifiers (GSC) to alleviate the over-fitting problem of standard classifiers [7]. They constructed a Spatial-Smooth Sparse Linear Discriminative Analysis (SSLDA) classifier to demonstrate the power of GSC. SSLDA has good performance for the Picture versus Sentence study provided by Mitchell [8].

3 Proposed Method

3.1 Regions of Interest

In this paper, we followed Mitchell et al. [8] to mark up the brain with 25 anatomical Regions of Interest (ROIs). They included: calcarine sulcus (CALC), dorsolateral prefrontal cortex – left & right (LDLPFC, RDLPFC), frontal eye fields – left & right (LFEF, RFEF), left inferior frontal gyrus (LIFG), inferior parietal lobule – left & right (LIPL, RIPL), intraparietal sulcus – left & right (LIPS, RIPS), opercularis – left & right (LOPER, ROPER), posterior precentral sulcus – left & right (LPPREC, RPPREC), supramarginal gyrus – left & right (LSGA, RSGA), superior parietal lobule – left & right (LSPL, RSPL), temporal lobe –left & right (LT, RT), triangularis – left & right (LTRIA, RTRIA), supplementary motor areas (SMA), inferior temporal lobule – left & right (LIT, RIT). A structural image which captures the static physical brain structure at high resolution was used to identify the anatomical regions of interest, using the parcellation scheme of Caviness and Rademacher [9].

3.2 Voxel Activity

The most common approach for feature selection when training classifiers is select the features that best distinguish the target classes. In fMRI data, not only the data that describes the mental states can be considered but also the data of non-state can be considered too. This kind of data is corresponding to the fixation or rest condition which contains the data observed when the subject is generally at rest. In this paper, we follow Mitchell's definition [8] for voxel discriminability and voxel activity:

- Voxel discriminability indicates how well the feature distinguishes class 1 from class 2.
- Voxel activity indicates how well the feature distinguishes class 1 or class 2 from the zero signal class.

By using the voxel activity, instead of selecting the features that best describe the correlation between-classes, we can choose features that best describe the mental state. Figure 1 illustrates the definition of voxel activity and voxel discriminability. In this paper, we measure the voxel activity by computing the Fisher Discriminant Ratio for every feature.

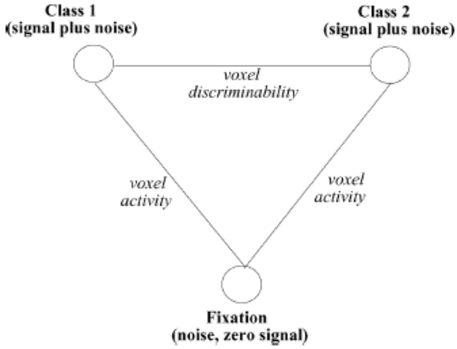

Fig. 1. Voxel discriminability and voxel activity [8]

4 Experimental Result

4.1 Data Description

We used the StarPlus data collected by Mitchell et al. for validation [8]. This data was conducted from six human subjects who were shown a sequence of sentences and a simple picture. We have to train a classifier to distinguish whether the subject is seeing a picture or reading a sentence. The pictures simply were geometric arrangements of symbols such as +, *, @, $, --. For each subject, we trained a classifier of the form:

f : fMRI-sequence (t, $t+8$) → {Class1, Class2}

where t is the starting time of stimulus. Signals in the interval of 8 seconds are considered to avoid lacking the brain activity.

Each subject includes 80 samples, 40 samples for each label. Table 1 shows the number of all features of each subject. Generally, each sample includes approximately 80,000 features.

Table 1. Data Description

Subject ID	*04799*	*04820*	*04847*	*05675*	*05680*	*05710*
Number of features	79184	80240	75168	82160	80992	74144

4.2 Evaluation

We firstly choose the most active ROIs by considering the performance of each region in our study. In our experiments, a set of ROIs: {CALC, LIPL, LT, LTRIA, LOPER, LIPS, LDLPFC} produced the best accuracy for our studies. We then extract the most active voxels from these ROIs to build the classifier.

For evaluating the classification performance, we applied k-fold cross validation with k = 10. The average accuracy was computed and compared to other methods such as all features, iPCA [3], and ROIs. Our proposed method will be described as ROIs+FDR with 250 features selected and performed by using GNB classifier. Table 2 shows the classification accuracy of our method for each human subject and the comparison with other methods. For all subjects, our proposed method had classification accuracy much higher than the others. Table 3 shows the comparision between the proposed method and the method of using voxel discriminability with the same measurement and classifier which are FDR and GNB. The voxel activity provides high accuracy for all of subjects while the voxel discrminability cannot achieve a good performance for subject 04820 and 05680.

Table 2. Classification result of single subject

Feature Selection	*04799*	*04820*	*04847*	*05675*	*05680*	*05710*
All features	56.75%	57.5%	75%	58.75%	67.5%	70%
ROIs	61.5%	70%	97.5%	75%	80%	80%
iPCA	80%	80%	90%	88.75%	78.75%	85%
ROIs+FDR	92.5%	97.5%	100%	98.75%	95%	95%

Table 3. Voxel Discriminability & Voxel activity

	04799	04820	04847	05675	05680	05710
Voxel Discriminability	91.25%	77.5%	98.75%	90%	85%	92.5%
Voxel Activity	92.5%	97.5%	100%	98.75%	95%	95%

5 Conclusion

In this paper, we have presented a new approach for classifying specific cognitive states of a single subject from fMRI data. By selecting the most active features with highest FDR values from several ROIs, we achieved a set of the most powerful discriminative features. The experimental results showed that our proposed method had a good performance with the highest accuracy compared to the other ones. In the future, we will apply this method to another kind of study and dataset to solve the problem of classifying human cognitive states. We will also extend to the problem of detecting multiple-subject cognitive states.

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